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MICROENTERPRISE CREDIT: IS THERE A NEED FOR SUBSIDY?

by

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Abstract

An empirical analysis of credit constraints is undertaken using an endogenous switching regression model. The empirical results clearly show the potential positive effect of credit expansion for microenterprises. Contrary to conventional credit impact studies, however, the results suggest that microentrepreneurs are potentially capable of realizing high marginal rates of return, so that there is no justification for subsidized rates of interest for microenterprise credit.

Microenterprise credit: Is there a need for subsidy?

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Introduction

Understanding the effect of credit constraints on the production behavior of microenterprises is essential to effective and realistic policy-making for microenterprise development.[1] This is particularly important in developing countries where credit constraints are more often the result of lack of access to formal sources of credit (Ho 1980, Anderson and Khambata 1981, Liedholm 1989, Duggleby et al. 1992, among others). Microentrepreneurs are more often perceived to be discriminated against in formal credit markets because of their lack of adequate and acceptable collateral (Binswanger and Sillers 1983, Eswaran and Kotwal 1986, 1990). Hence, targeted credit at subsidized rates of interest is justified on the grounds that it breaks the entry barrier to formal finance and allows the relaxation of credit constraints faced by microenterprises.

The assessment of the expected productivity gains obtained from an increased supply of credit is, however, an important issue that is underemphasized in subsidized credit programs. David and Meyer (1980) contend that it is difficult to to ascertain whether subsidized credit programs have a positive impact on production because of the fungibility of credit. If credit simply displaces another source of finance such as savings or if it is diverted to finance consumption or other household activities, then it may have no effect on production. Moreover, the issue that microenterprises are indeed credit constrained has frequently been accepted as fact but never really empirically supported or validated. This paper contributes to the limited literature that seeks to provide empirical support for the effectiveness of credit policy for microenterprise development. It shows that there is empirical support to believe that microenterprises are credit constrained as a result of the prevailing inefficiencies in the credit market. In addition, relaxing the credit constraint through through an increased access to credit is shown to have a positive effect on production for microenterprises.

The Methodology

The effect of relaxing of a credit constraint can be analyzed using an endogenous switching regression model.[2] Let Q(.) be the anticipated output supply, defined as a function of loan size

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[1] The analysis of the effect of credit constraint on the production of microenterprises is done within a household model framework in Lapar (1994).

[2] This is an adaptation of the model used by Sial and Carter (1992).

and other characteristics. Output for an enterprise "i" is produced according to one of the two production regimes:

$$(1) \qquad Q_i = \begin{cases} Q_{ic} = \alpha' \ell_i + \beta' c z_i + (v_{ic} + \epsilon_{ic}) \text{ if a borrower,} \\ Q_{in} = \beta'_n z_i + (v_{in} + \epsilon_{in}) \text{ if a nonborrower,} \end{cases}$$

where the base regime is the nonborrowing case. The implicit assumption in this framework is that microenterprise borrowers are able to relax their credit constraints. The right hand side variables include the observable and unobservable variables, where the observables are the ℓ_i and z_i. The vector ℓ_i is a quadratic expansion of the loan amount L_i. The impact of loans on output supply is given by $\alpha'\ell_i$, a nonlinear function of L_i which allows for diminishing returns to loans. On the other hand, the vector z_i includes variables that account for market opportunities, fixed factors of capital and labor, and entrepreneurial characteristics, among others. The parameters β_j $(j=n,c)$ give the impact of the observable variables on output supply and are allowed to vary between the two regimes in (1) to allow for the possibility that a relaxed financial constraint may permit an individual to earn larger returns from a given market opportunity and level of fixed factors. The latent variables are divided into those that are known (the v_i's) and those that are not known (the ϵ_i's). The v_i's give the effect of inherent enterprise and entrepreneur characteristics such as managerial and entrepreneurial skills on output supply. While these are known to the individual, they are not observed by the econometrician. It can be assumed that this latent variable is scaled such that $E(v_i)=0$ for an individual selected at random from the overall population of borrowing and nonborrowing microentrepreneurs. The v_i's are allowed to differ across the two production regimes in the full switching regression specification to accommodate the productivity effect of differences in the attributes between borrowers and nonborrowers (e.g., a relaxed credit constraint may result in larger returns to latent managerial ability). The ϵ_i's are the conventional, unanticipated random supply shocks that are unknown to the entrepreneur at the time the production decisions are made and it is assumed that $E(\epsilon_i)=0$.

Estimation of the parameters in the output supply equation (1) is complicated by the fact that credit status is endogenously determined in a way that may be systematically related to the expected credit effects (Carter 1989). Under this endogenous sorting, it is likely that borrowers have systematically different attributes from nonborrowers. Thus, while $E(v_i)=0$ for an individual randomly chosen from the overall population, it seems likely that the latent variable v_i has a nonzero conditional expectation for the two non-randomly sorted subsamples of borrowers and nonborrowers. There is a need, therefore, to specify the non-random process that sorts individuals into borrowers and nonborrowers in order to obtain consistent estimates of the production regime parameters and identify the effect of credit.

The process that sorts borrowers and nonborrowers into the two regimes involves the decision of the individual to apply for the loan and the decision of the lender to give the loan. This implies two selection criterion functions, where, say, I_1^* refers to the individual's decision whether or not to apply for a loan, and I_2^* refers to the lender's decision whether or not to grant the loan.[3] The analysis of models with more than one selection criterion function like this one will depend critically on whether the two decisions are independent or correlated; that is, whether or not the covariances of the error terms in the two criterion functions are zero. If the covariance is zero, implying independence, then the estimation of the parameters of the model is feasible and tractable. However, if the covariance is not zero, implying non-independence, which in the case of the borrower and lender decision is a realistic assumption, then the estimation becomes more difficult because the expressions of the expected values of the error terms "get very messy." (Maddala 1983, p.282). In this case, the bivariate probit method is used to estimate the criterion functions. (See Fishe et al. 1981, for example). This approach is deemed not feasible in this study because of the lack of information on the decision-making process of the lenders, i.e., there is no information in the data set pertaining to the factors affecting lender's decisions whether or not to grant a loan. Thus, a second best approach is used wherein a single probit equation, which is an approximation of the two-probit equations, is specified as the criterion function.[4] Let this single probit equation be termed the credit status equation which should include factors affecting the individual's decision to apply for a loan and the lender's decision to grant the loan. In the absence of information from the lender's side, factors from the borrowers' side are used to infer lender behavior.

Credit status can be represented by the binary variable D_i which equals one if a borrower and zero otherwise. D_i can be modelled as a result of a latent credit access variable, $\mathcal{L}_i$, which is scaled such that an individual becomes a borrower when $\mathcal{L}_i > 0$. A reduced form specification for latent credit access can be written as:

$$(2) \qquad \mathcal{L}_i = \gamma' x_i + \eta_i ,$$

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[3] Note that the individual's decision whether or not to apply for a loan and the lender's decision whether or not to grant a loan can be modelled as either as a sequential-decision process or a joint-decision process(see Maddala 1983). In both cases, there should ideally be two criterion functions to represent the individual's and the lender's separate decision choice, where the individual's criterion function can represent the demand for credit and the lender's criterion function, the supply of credit. However, if marginal and conditional inferences are needed to be made in the analysis, then the sequential-decision selection approach to model the criterion function may not be the appropriate approach (see Maddala 1983). The resulting truncation in the sample has been shown to affect the quality of the estimates of the parameters of the selectivity criterion even if it is still possible to correct for the selectivity bias in the OLS estimates of the parameters of the second stage equation (Maddala 1983, p.267). An alternative way of modelling the criterion function is to consider the individual's decision whether to apply for a loan and the lender's decision whether or not to grant a loan as a joint decision. This approach can be justified by the fact that what we actually observe is whether an individual is a borrower or a nonborrower and we do not observe the individual decisions of the individual borrower and the lender.

[4] It is recognized that the second best approach will not usually result in estimated parameters that are comparable with those obtained using the ideal model. In this case, the use of the single probit equation to approximate the two-probit criterion functions may result in biased estimates of the parameters of the criterion function.

where x_i is a vector of variables that determine credit access, γ is a vector of parameters, and η_i is an error component reflecting random and latent factors that influence credit access. Thus, the sample separation process can be written as:

$$(3) \qquad D_i = \begin{cases} 1 \text{ if } \mathcal{L}_i = \gamma' x_i + \eta_i > 0, \text{ or } \eta_i > -\gamma' x_i \\ 0 \text{ otherwise.} \end{cases}$$

The expected output supply conditional on the endogenous sample separation process and observable characteristics can then be written as:

$$(4a) \qquad E(Q_{ic} | D_i = 1) = \beta'_c z_i + \alpha' \ell_i + E(v_{ic} | D_i = 1)$$

$$(4b) \qquad E(Q_{in} | D_i = 0) = \beta'_n z_i + E(v_{in} | D_i = 0)$$

where conditioning on the observable variables z has been suppressed.[5] From (3) and (4), the full endogenous switching regressions system[6] can then be written as:

$$(5a) \qquad D_i = \begin{cases} 1 \text{ if } \eta_i > -\gamma' x_i \\ 0 \text{ otherwise.} \end{cases}$$

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[5] Note that the conditional expectations on the right hand side of equations (4a) and (4b) can be written as: (i) $E(v_{ic}|D_i=1) = E(v_{ic}|\eta_i > -\gamma' x_i)$ and (ii) $E(v_{in}|D_i=0) = E(v_{in}|\eta_i < -\gamma' x_i)$. The problem of intrinsic productivity differences between borrowers and nonborrowers can be clearly seen from (i)and (ii). If latent productivity attributes are systematically related to credit status, then the conditional expectations in (4) will not be zero. For example, individuals with better entrepreneurial skills are likely to realize larger output supply (via v_{ic}) as well as have higher probability of obtaining credit under non-random sorting (via η_i), implying that $E(v_{ic}|D_i=1) > 0$ in the borrower subsample. Under these circumstances, estimating the output supply equation using OLS will not yield consistent estimates of the structural parameters because of the correlation between latent managerial skill and the observed loan amount. The direct output effect of latent managerial skill, in this case, is attributed to the observed loan amount with which it is correlated.

[6] The problematic correlation between the v_i and η_i indicates that the latter in fact provides information on the latent variable v_i. Thus, the parameters of interest can be consistently estimated by using this information to control for the latent characteristics v_{ic} and v_{in}. This can be done by making distributional assumptions to substitute for the latent information. From the sample selection literature, it is possible to separately identify the effect of latent individual attributes and obtain consistent estimates of the structural parameters of the output supply function conditional on assumptions about the error structure. Following Maddala (1983), assume that the error vector (η_i, v_{ic}, v_{in}) is distributed multivariate normal with zero expectations and positive definite covariance matrix. This assumption allows the specification of the full switching model, where $\rho_c = Cov(\eta_i, v_{ic})/Var(\eta_i)$ and $\rho_n = Cov(\eta_i, v_{in})/Var(\eta_i)$ are the population regression coefficients relating the v_{ic} and v_{in}, respectively; $\lambda_i^c = \phi(C_i)/\Phi(C_i)$ and $\lambda_i^n = \phi(C_i)/1-\Phi(C_i)$ are the estimates of η_i given borrower type and $C_i = \gamma' x_i / Var(\eta_i)$; $\phi(.)$ and $\Phi(.)$ are the standard normal density and cumulative distribution functions, respectively. The parameters of this system can be estimated using maximum likelihood methods. Heckman proposes a two-stage procedure for estimating consistent but less efficient parameters of (5) (Maddala 1983). Consistent estimates of β may be obtained through separate OLS regressions of the two conditional output supply functions in (5). Alternatively, it is possible and often desirable to estimate (5) using all the observations in Q_i (Maddala 1983).

(5b) $E(Q_{ic}|D_i=1) = \beta'_c z_i + \alpha'\ell_i + \rho_c\lambda_i^c$

(5c) $E(Q_{in}|D_i=0) = \beta'_n z_i + \rho_n\lambda_i^n$.

Note that

(6) $E(Q_i) = E(Q_{ic}|D_i=1)\mathrm{Prob}(D_i=1) + E(Q_{in}|D_i=0)\mathrm{Prob}(D_i=0)$, so that

(7) $E(Q_i) = \beta'_n z_i + \delta'[\Phi(C_i)z_i] + \alpha'[\Phi(C_i)\ell_i] + (\rho_c - \rho_n)\phi(C_i)$.

From (7), the direct credit effect parameters, the α, and the indirect credit effect parameters, the δ and the $(\rho_c - \rho_n)$ can be estimated. While the direct effect parameters give the increase in output supply due to the use of loans, the indirect credit effects represent the additional returns to observable and unobservable endowments when credit is used. If the use of credit does not enhance the returns to other factors, i.e., both δ and $(\rho_c - \rho_n)$ are equal to zero, then (7) reduces to the following equation:

(8) $E(Q_i) = \beta'_c z_i + \alpha'[\Phi(C_i)\ell_i]$.

Equation (8) is a restricted form of (7) wherein credit has direct effects only.

Credit Effect Measures

The credit effect measures[7] to be used in determining the effect of credit on output are defined as follows:

(9a) Random credit effect:

$$E(Q_{ic}-Q_{in}) = [\beta'_c z_i + \alpha'\ell_i + E(v_i|D_i=1)]-[\beta'_n z_i + E(v_i|D_i=0)] = \delta' z_i + \alpha'\ell_i$$

(9b) Counterfactual credit effect for borrowers:

$$E(Q_{ic}|D_i=1) - E(Q_{in}|D_i=1) = [\beta'_c z_i + \alpha'\ell_i + E(v_{ic}|D_i=1)] - [\beta'_n z_i + E(v_{in}|D_i=1)] = \delta' z_i + \alpha'\ell_i + (\rho_c - \rho_n)\lambda_i^c.$$

(9c) Counterfactual credit effect for nonborrowers:

$$E(Q_{ic}|D_i=0) - E(Q_{in}|D_i=0) = [\beta'_c z_i + \alpha'\ell_i + E(v_{ic}|D_i=0)] - [\beta'_n z_i + E(v_{in}|D_i=0)] = \delta' z_i + \alpha'\ell_i + (\rho_c - \rho_n)\lambda_i^n.$$

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7 See Carter (1989) and Sial and Carter (1992).

The random credit effect measure determines the effect of credit were it given to an individual selected at random from the overall population of rural nonfarm entrepreneurs. Equation (9a) shows the expected effect of credit if it were randomly assigned to an average individual without any intervening systematic selection or conditioning on the basis of the unobserved individual characteristics. Hence, the expected value of latent attributes for such an individual is zero. On the other hand, the counterfactual credit effect measure compares the output anticipated by an individual under the actual credit status with the output level that would be anticipated by that same individual in the counterfactual state (Tunali 1985, Carter 1989). Note that both counterfactual measures are in fact the sum of the random credit effect and the gains or losses the individual would anticipate given the latent characteristics. While the random credit effect can show the effect of credit on the output supply of an individual with the same observable attributes as the other individuals in the sample, the counterfactual credit effect can indicate the effect of credit on the output of individuals who choose to be or not to be borrowers. Thus, the hypothesis of a positive credit effect can be tested by looking at the estimates of potential output under the counterfactual state for both borrowers and nonborrowers. Notice that both the random and counterfactual effects are measures of the total effect of credit on output supply. In order to determine the marginal effect of additional credit on output supply, we use the marginal credit effect which is defined as the partial derivative of output with respect to loan amount. This measure is shown as:

$$(10) \quad \partial E(Q_1 | D_1)/\partial L_1 = \alpha'[\Phi(C_1)].$$

An estimate of the marginal effect of credit can be used to indirectly test the hypothesis that nonborrowers are credit constrained. If the estimated marginal returns to credit are greater than the shadow price of credit at zero loan, this implies that nonborrowers are credit constrained to the extent that an additional unit of loan would result in more than a unit increase in output.

The credit access equation is empirically estimated as a function of factors that explain the borrower's demand for and supply of credit such as the value of fixed assets, total assets, and financial assets owned by the entrepreneur, previous year's income, number of years the enterprise has been operating, age of the owner/operator, number of years spent in school (as a measure of educational attainment), and a dummy variable for bank-client relationship, i.e., existence of a bank account, which equals one if the operator has a bank account and zero otherwise. Dummies for gender, type of activity undertaken, and province where the enterprise operates are also included.

The output supply equation is empirically specified as a function of fixed and non-fixed inputs and other observable characteristics such as the entrepreneur's previous work experience, the average number of hours the enterprise operates during the period 1991, number of years the enterprise has been operating, among others. A quadratic form of the variable loan amount is included to account for the direct effect of credit on output. The loan variable represents the total value of loans received by borrowers during the period 1989-1991, i.e., the preceding two years and the current year of operation covered in the study. Dummy variables for province and type of enterprise activity are also included in the equation. The dependent variable is the logarithm of the value of output.

The data used in estimating the model were obtained from a survey of microenterprises in the Visayas region of the Philippines. The survey area included the provinces of Iloilo, Negros Occidental, Cebu, and Bohol where a higher degree of economic activity is observed relative to the other parts of the Visayas region. With Visayas considered as one of the growth centers in the Philippine government's latest Medium-Term Development Plan, it can be a potential hub of economic activity in the coming years implying better economic opportunities for microenterprises in the region. There were 400 sample enterprises in the data set, of which 125 were engaged in manufacturing, 164 with trading, and 111 with services (see Lapar 1994 for the description of the sampling design).

Empirical Results

The credit effects are estimated using the coefficients of the restricted model[8] (equation 8). Note that of the estimated coefficients in the loan vector, namely the loan variable and its square, only the coefficient for the loan variable is statistically significant at the 5 percent level (see Table 1). A test of joint significance of the two variables revealed, however, that the joint hypothesis that the coefficients are equal to zero is rejected at the 5 percent level. Hence, both coefficients are used in computing the credit effects. Table 2 shows the estimates for the credit effect measures discussed above. The random credit effect (equation 9a) is estimated to be 0.23 and is statistically significant at the 1 percent level, implying an increase of 23 percent in output for an average borrowing entrepreneur. The estimated random credit effect also empirically supports the hypothesis that non-credit users will potentially increase their output when credit is used. (Note that the random credit effect is equal to the counterfactual credit effect under the restricted specification of the switching regression model.) The marginal effect of credit is also shown to be positive (equation 10). At the mean loan size, credit is estimated to have a marginal effect of 1.73, implying that the marginal output effect of one morepeso of loan is ₱1.73 and this is statistically significant at the 1 percent level. This estimated effect also implies that at the observed mean loan size of ₱20 thousand, the marginal return to credit is larger than the average cost of credit which is about 35 percent. When evaluated at zero loan size, the marginal credit effect is estimated to be 1.79, implying a potential increase of more than a peso in output for every peso of loan. This estimate also indicates a 79percent shadow price of credit, suggesting a potentially high return to credit and indirectly supporting the hypothesis that nonborrowers are credit constrained.

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[8] The restricted model was estimated to reflect the empirical results that borrowers do not obtain additional returns from observable variables and unobservable attributes, i.e., the estimated coefficients of δ and (ρ_c -ρ_n) are not statistically significantly different from zero. See Lapar (1994) for a detailed discussion.

Table 1: Estimated coefficients of the endogenous switching regression model

	Full Switching Model		Restricted Model
	All	Borrower	Variable Differential
Constant	-1.295507	9.251535	4.360621
	(-0.510)	(2.364)**	(6.829)*
No. of family	-0.017823	0.666508	0.273229
workers	(-0.073)	(1.352)	(2.800)**
No. of hired	-0.180227	0.885918	0.167336
workers	(-1.018)	(1.303)	(2.269)**
Total assets	0.290907	-0.281013	0.145180
	(2.560)*	(-1.340)	(3.675)*
Working capital	0.526370	-0.312765	0.394831
	(6.073)*	(-1.672)	(12.298)*
Cost per hour	0.412604	-0.681619	0.137971
of labor (in pesos)	(2.574)*	(-1.002)	(2.391)**
Age of enterprise	0.176075	-0.248552	0.074787
	(1.311)	(-0.902)	(1.369)
Household size	-0.044101	0.208046	-0.012624
	(-0.188)	(0.427)	(-0.137)
Ave. no. of hours	0.884029	-1.002134	0.344517
operated	(1.531)	(-0.891)	(1.713)***
Mfg. (dummy)	0.258388	-0.882149	-0.255514
	(0.437)	(-0.852)	(-2.037)**
Trdg. (dummy)	0.334885	-0.315130	-0.023815
	(0.512)	(-0.216)	(-0.191)
Bohol (dummy)	-0.763465	0.270541	-0.596292
	(-1.888)***	(0.285)	(-3.631)*
Iloilo (dummy)	-0.312807	0.148047	-0.109236
	(-0.656)	(0.141)	(-0.816)
Cebu (dummy)	0.594503	-0.476475	0.468399
	(1.884)***	(-0.607)	(3.669)*
Experience (dummy)	0.112733	0.128780	0.147340
	(0.475)	(0.257)	(1.513)
Loans		0.00001087	0.000011758
		(2.213)**	(2.448)**
Loans squared		-1.04995×10^{-11}	-1.11392×10^{-11}
		(-1.263)	(-1.366)
Pdf	--	2.685880	--
		(1.358)	
Adj. R^2	0.72	0.70	0.70

Note: Figures in parentheses are t-values.
*Significant at 1 percent, **Significant at 5 percent, ***Significant at 10 percent.
Source of Data: DRD-Survey of Rural Nonfarm Enterprises, 1992.

Table 2: Estimated values of credit effects

Effect	Estimated Value
Random credit effect (at mean loan size)	0.23079 (0.000004)*
Marginal credit effect (at mean loan size)	1.7329 (0.3242)*
Marginal credit effect (at zero loan size)	1.7940 (0.3357)*

Note: Figures in parentheses are standard errors. Under the restricted switching regression specification, random credit effect is equal to the counterfactual effect.
* Significant at 1 percent.
Source of Data: Table 1.

Some Policy Implications

The empirical results obtained in the study raise several issues pertaining to the development of microenterprises as well as rural credit market policies in the Philippines. Despite efforts to liberalize the rural credit market and make it more efficient, the prevailing conditions still have not made a substantial impact in addressing the credit constraint problem of microentrepreneurs. On the other hand, the empirical results clearly indicate a potential positive impact of microenterprise credit expansion. This result is consistent with the results of traditional credit impact studies in the past. However, contrary to the usual policy prescriptions of traditional credit projects (e.g., subsidized interest rates, creation of institutions for direct targeting of credit to a particular clientele, among others), the results obtained from this study point to a different set of policy implications. The empirical results clearly suggest that the policy of no interest rate subsidy for loans to microenterprises is justified. There has always been a perception that the only way to successfully implement a microenterprise credit program is through subsidized loan rates to a specific group or clientele. There are strong indications in this study that microentrepreneurs are capable of realizing high rates of return on capital so that they are potentially capable of paying market rates of interest.

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